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## Reputation, honesty, and cheating in informal milk markets in India

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Markus Kröll - Devesh Rustagi

# Reputation, Honesty, and Cheating in Informal Milk Markets in India

SAFE Working Paper No. 134

**SAFE | Sustainable Architecture for Finance in Europe**

A cooperation of the Center for Financial Studies and Goethe University Frankfurt

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## Non-Technical Summary

Markets with asymmetric information provide a fertile ground for cheating, which is a widespread problem, especially in developing countries. In order to counteract the incentives generated by asymmetric information, economists have conventionally focused on extrinsic factors, such as reputation and enforcement; the assumption being that individuals are inclined to cheat unless such factors prevent them from doing so. Yet field evidence underlines that individuals display persistent heterogeneity in cheating behavior even in the absence of extrinsic incentives. This intriguing observation together with the growing literature in economics on psychological costs of lying suggests that intrinsic motivation for honesty might also play an important role in the decision to cheat. In this paper, we examine in the field whether variation in the motivation for honesty among sellers explains differences in cheating behavior of these sellers in natural markets with asymmetric information.

A major challenge in establishing this association is to obtain a high-quality measure of motivation for honesty at the individual level. Because separating motivation for honesty from other motives is tedious while using field data, economists resort to laboratory experiments, which allow for careful separation of confounding motives. One popular experiment involves the repeated use of a random device (e.g. toss of a coin, roll of a die) and then applying statistical distributions on self-reported outcomes by the participants to classify them into honest and dishonest types. However, such a binary classification does not fully capture the heterogeneity in cheating behavior. We therefore present a novel experimental design to obtain high-quality measures of motivation for honesty at the intensive margin at the individual level. We then combine these measures with a unique objective field outcome on cheating of the same individual to investigate the importance of motivation for honesty in natural markets with asymmetric information.

Our study takes place in an important market for human health and nutrition - informal markets for buffalo milk in Delhi, India. These markets provide a unique setting to investigate our research question. We use the percentage of added water in milk as our measure of cheating behavior in the field. To obtain this outcome, we hire local assistants to pose as occasional customers and buy milk from each milkman. We then test these samples for added water using an ultrasonic milk analyzer, specifically calibrated for the Indian milk market. The milk analyzer provides us with the precise percentage of added water in milk, i.e. milliliter of water added to 1 liter of pure milk. The results reveal substantial variation in added water across milkmen.

To measure the milkmen's motivation for honesty, we conduct a behavioral experiment. Milkmen have to roll a die 40 times and are paid 2 Indian rupees (INR) for each point they report on a game sheet. The die we use is Bluetooth enabled, which transmits the actual outcomes of the rolls. This novelty allows us to contrast reported with actual outcomes and hence construct precise measures of motivation for honesty. We find considerable differences in the individuals' motivation for honesty. At the extensive margin, we find that 12.5 percent of the milkmen are classified as dishonest using statistical distributions. However, there is large variation in the degree of dishonesty even among the dishonest milkmen, which we capture via our measure at the intensive margin. This measure is the number of over-reported rolls, computed as the number of times the reported outcome exceeds the actual one. On average, milkmen over-reported in 3.63 rolls, but there is a wide variation in over-reporting, ranging from 0 to 27 rolls.

We then combine our experimental measures with the field outcome on cheating of the same milkman to test whether motivation for honesty explains the large variation that we observe in the field outcome on cheating. We find a strong and highly significant association between motivation for honesty and cheating behavior in milk markets. Dishonest milkmen add

# **Reputation, Honesty, and Cheating in Informal Milk Markets in India**

Markus Krölland Devesh Rustagi<sup>1</sup>

## **Abstract**

Sellers display astounding differences in their cheating behavior, even in developing countries with weak enforcement of rules. Using the context of informal milk markets in India, we examine the role of reputation and norms of honesty as potential explanations. Our results show that individuals cannot verify milk quality, which weakens the scope of reputation-based mechanisms. But a strong correlation exists between milk quality and norms of honesty, measured using a novel behavioral experiment. Price collusion allows for the co-existence of honest and dishonest milkmen within a market. Norms of honesty can mitigate market inefficiency under the right institutional environment.

JEL: C93, D06, D08, O13, Q01

Keywords: Cheating, informal sector, reputation, norms of honesty, milk markets, India.

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## I. Introduction

In developing countries, the informal sector accounts for up to half of the economic activity: firms in this sector are unregistered, carry out transactions in cash, do not pay taxes, and evade regulations (La Porta and Shleifer 2014). Another feature of developing economies is the weak willingness or capacity of government to enforce rules (Hallward-Driemeier and Pritchett 2015). Under these conditions, in markets with product quality uncertainty, sellers have a strong incentive to cheat – replace good quality with poor quality and sell it at the same price as good quality. Yet, informal markets do not converge to an equilibrium in which sellers cheat by the maximum possible extent. Rather, extensive field evidence underlines large variation in the extent of cheating even within the same sector, with many sellers refraining from cheating altogether (Liu et al. 2010, FSSAI 2011, Souza et al. 2011, Faraz et al. 2013). Understanding why sellers vary in their cheating behavior is important for designing optimal contracts and government interventions.

An important view among economists is that individuals cheat rationally, i.e. when the benefits exceed the costs of cheating. Accordingly, several studies have shown the importance of mechanisms that affect these costs, such as monitoring, enforcement, and liability (Nagin et al. 2002, Dulleck and Kerschbamer 2006, Olken 2007, Dulleck et al. 2011, Duflo et al. 2013). However, when recourse to such mechanisms is limited, as in incomplete contracts, individuals may rely on building long-term relationships based on reputation to deter short-term opportunism against future benefits (McMillan and Woodruff 1999, Macchiavello and Morjaria 2015).

In this paper, we investigate what could possibly explain the large variation in cheating in markets where both enforcement and reputation are unlikely to matter. One plausible candidate is that sellers are heterogeneous in their intrinsic motivation to cheat. Recent studies in economics show that many individuals have social preferences and norms of honesty (Fehr et al. 1997, Gneezy 2005, Fisman and Miguel 2007, Fischbacher and Föllmi-Heusi 2013, Gächter and Schulz 2015).<sup>2</sup> However, the tenability of this explanation in

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<sup>2</sup> For instance, Fehr et al. (1997) document the importance of social preferences in the enforcement of contracts in a laboratory experiment. Fisman and Miguel (2007) study the role of norms of corruption in explaining opportunistic behavior without and with enforcement options among diplomats. Hanna and Wang (2015) examine the role of dishonesty on selection into public sector in India. Other studies use self-reported outcome in the context of free riding on public transport, teacher assessment of students, and overpayment in laboratory

a market setting is puzzling and raises an important question: how can honest sellers survive in a market? Dishonest sellers may set prices below the marginal cost of production of honest sellers, driving the latter out of the market (Akerlof 1970). Thus, for norms of honesty to serve as a credible explanation behind the large variation in cheating in markets, another mechanism may be needed.

This paper provides evidence on: (i) large heterogeneity in norms of honesty among sellers; (ii) variation in norms of honesty explains differences in the cheating behavior of sellers; (iii) the co-existence of honest and dishonest sellers within a market is made possible because of price collusion, which allows sellers to earn joint monopoly profits; and (iv) several features of the field setting ensure the stability of such collusive arrangements. These results suggest that while norms of honesty mitigate one market imperfection, another market imperfection creates an institutional environment conducive for such norms to operate.

Our study takes place in informal markets for buffalo milk in India, which suffer from product quality uncertainty. These markets account for 80-90 percent of the milk sold in India, which itself is the largest producer of milk in the world (Delgado and Narod 2002, FAO 2013, Lindhal et al. 2017). Milk markets in India offer large variation in cheating: a national survey found that while 68 percent of the milk samples were adulterated with water, 32 percent were deemed unadulterated (FSSAI 2011). Adulteration of milk with water poses a concern for public health, as milk is a vital source of nutrition, accounting for 13 percent of the protein intake and 7 percent of the consumption expenditure in India (Varadharajan et al. 2013). Moreover, because the added water is contaminated, it additionally exposes customers to pollutants.

Three important features of the informal milk markets are worth noting. First, even though the law prescribes punishment for milk adulteration, monitoring of milk markets is rare and prosecutions almost never happen. Second, although individual milkmen cater to customers that differ in the duration of repeated interaction, their production technology does not allow them to differentiate customers either in quality or price of the milk sold. Third, milkmen sell milk directly to their customers without any intermediaries, allowing us to cleanly trace out the cheating party by observing final milk quality. These features limit the

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experiments (Dai et al. 2016, Cohn and Marechal 2016, Potters and Stoop 2016). Cabrales et al. (2010) examine the scope of social preferences and strategic uncertainty in a laboratory market.

role of enforcement and reputation in mitigating cheating in informal milk markets. In addition, they also allow us to map tightly the association between norms of honesty and milk adulteration.

We start by measuring a milkman's cheating behavior by assessing the amount of water added to a liter of milk sold to customers. A team of assistants, unknown to milkmen, purchased a liter of buffalo milk from each milkman in a one-shot interaction. The milk was then tested via an ultrasonic milk analyzer, which uses the freezing point of milk to determine the precise level of added water. We find that milkmen vary widely in their cheating behavior: while some add as little as 4 percent water to milk, others add as much as 37 percent, the average being 18 percent (s.d. 7.5).<sup>3</sup> This variation is not due to natural variation of water in milk, as the freezing point of milk is a biological constant that is very difficult to tamper with. It is not due to differences in weather or buffalo breed either, as these were held fixed in our study. In fact, a second sample of milk obtained for a sub-set of milkmen in our study shows strong persistence in cheating behavior.

We proceed by confirming the unlikely role of reputation in explaining the variation in milk quality. Theory suggests that for reputation-based mechanisms to work, customers need a weak signal on quality (Levin 2003, Board and Meyer-ter-Vehn 2013, Baker and Choi 2016, Ganuza et al. 2016). We investigate the plausibility of such a signal being present by conducting an incentivized milk-testing tournament. Specifically, we ask milkmen to predict the level of water in five samples of milk that we adulterated ourselves in varying degrees. We find that milkmen, who are experts on milk quality, are unable to distinguish even pure milk from highly diluted milk. Moreover, when milk samples containing the same level of added water were presented twice, milkmen rated these very differently. These findings suggest that obtaining even a weak signal on milk-quality is extremely difficult, which limits the scope of reputation in mitigating cheating in our setting and bear semblance to laboratory findings by Dulleck et al. (2011).

Next, we examine the scope of norms of honesty in mitigating cheating in milk markets. We combine field data on cheating in milk sold by milkmen to customers with norms of honesty of the same milkmen. Norms of honesty of individual milkmen are elicited via a behavioral experiment that involves the use of a random device (Fischbacher and

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<sup>3</sup> The machine error rate is  $\pm 3$  percent.

Föllmi-Heusi 2013, Hanna and Wang 2015). Milkmen are asked to roll a die privately 40 times and are paid for each self-reported point. This allows us to classify milkmen whose self-reported outcomes exceed a critical threshold of the theoretical probability distribution of the random device as ‘dishonest’ and the rest as ‘honest’. However, heterogeneity in dishonesty is expected to go beyond this binary classification, as dishonest milkmen might also vary in their degree of dishonesty. We therefore augment our experimental design with a Bluetooth-enabled die, which allows us to obtain the actual outcome of the die rolls.<sup>4</sup> Contrasting self-reported with actual outcomes not only enables us to correct the sizable measurement error in the binary classification, but also to capture degrees of dishonesty among dishonest milkmen. Measuring the latter primarily as the number of over-reported rolls, we find that 50 percent of the milkmen report honestly in all their rolls, but the remaining 50 percent are dishonest and over-report in 1 to 27 rolls by 1 to 74 points.

We investigate econometrically the association between degrees of dishonesty and adulteration of milk, controlling for the price at which the milk sample was purchased, milkman specific characteristics, livestock related input factors, and fixed effects for the time of the day the milk sample was obtained, assistants who bought the milk, and the neighborhood where a milkman resides. Our results reveal a strong positive association between the degree of dishonesty and the percentage of added water in milk, which is significant at the 1-percent level. A one standard deviation increase in the number of over-reported rolls (6.6) is associated with an increase in added water by 3 percentage points, which is nearly one-half of the standard deviation of the mean added water to milk. Our measure of dishonesty explains up to 21 percent of the variation in the outcome, the largest of all covariates. The association is also economically large, as additional monetary gains from dishonesty turn out to be eight percent of a milkman’s monthly income.<sup>5</sup>

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<sup>4</sup> We designed our instructions carefully, such that, on the one hand, milkmen were not aware that the die is Bluetooth enabled, but on the other hand, we did not lie to them that their behavior in the experiment will never be observed. Our study is not unique in using such a design, as prominent laboratory (Andreoni 1988, Gächter and Thöni 2005) and field (Bertrand and Mullainathan 2004, Dizon-Ross et al. 2015, Das et al. 2016) studies also withheld information to study the effect of surprise re-starts, sorting by types, discrimination, and cheating respectively. As in previous studies, such a design allows us to obtain otherwise inaccessible data, which is essential to measure heterogeneity in honesty, without harming the subjects (see also Glennerster and Powers 2014) Although, we are able to reproduce our results using the binary measure of dishonesty, we show later that these results are prone to measurement errors that lead to biased estimates.

<sup>5</sup> We also find a strong positive association between dishonesty and the percentage of added water in the second sample, which is comparable in magnitude and significance to estimates from the full sample.



These results are puzzling as they allude to the co-existence of honest and dishonest milkmen within a market. Our survey data reveal that a plausible reason behind this coexistence could be price collusion. Milkmen collude within a neighborhood by fixing the price of milk and raising it collectively by a fixed amount every year. Repeated interaction, ease of monitoring, and severity of social sanctioning ensure self-enforcement of such collusive arrangements. Several market conditions identified in the literature further facilitate the stability of this collusion (Harrington 2006, Grout and Sonderegger 2005, White et al. 2013). These results suggest that under the right institutional environment, norms of honesty can mitigate market inefficiencies arising from product quality asymmetry, even when enforcement and reputation are unlikely to matter.

This paper contributes to the literature on cheating in markets, in particular in developing countries. Previous studies on this topic have mainly discussed the role of mechanisms that affect the pecuniary costs of cheating, such as monitoring and enforcement (Duflo et al. 2013, Nyqvist-Björkman et al. 2013), as well as reputation (McMillan and Woodruff 1999, Macchiavello and Morjaria 2015). Our paper adds to this literature by providing first evidence on the importance of norms of honesty under conditions where both enforcement and reputation are unlikely to play a role. In this aspect, our study complements a laboratory study by Dulleck et al. (2011), who find that a non-trivial share of sellers behave honestly by providing appropriate quality throughout the entire period of the experiment, even in the absence of verifiability and enforcement institutions. The authors postulate this result is probably due to social preferences and norms of honesty. Our paper fills this void by directly testing for the role of norms of honesty in mitigating cheating. Our results stand in contrast to those reported by List (2006), who finds that in a market for baseball cards, the (accurate) provision of product quality, which is consistent with social preferences, is actually due to reputational concerns and is only observed when third party verification is possible. Our paper clearly shows that norms of honesty matter even when enforcement and reputation have a limited role. One reason behind these contrasting results could be market power, which allows for honest types to co-exist in the market. In this sense, our paper also points towards the importance of market structure for cheating and corruption (Olken and Barron 2009, Banerjee et al. 2012) and also adds to the growing literature on the interaction between markets and morality (Bowles 1998, Falk and Szech 2013, Bartling et al. 2015).

The rest of the paper is organized as follows. Section II describes informal milk markets in India. Section III describes the design of the milk-testing tournament, data collection on cheating in milk markets, and the behavioral experiment we use to measure norms of honesty. Section IV presents our main results on the role of reputation and the degree of dishonesty in explaining cheating in milk markets, including several robustness checks, and factors ensuring collusion stability. Section V offers concluding remarks.

## II. Field Setting

Within India, we focus on informal milk markets in Delhi. In this section, we describe briefly the field setting including the structure of milk markets, quality of the milk sold, and the implication this might have for public health.

### *A. Informal milk markets in Delhi*

Informal milk markets in Delhi include ten outlying neighborhoods that are designated for dairy farming under the local zoning laws (DDA 1985). Each neighborhood is typically very dense, comprising many adjoining dairy plots that are of similar size (Figure 1) and were allotted on a license basis in the 1970s. A large majority of milkmen own a single built-up plot from which they run their dairy-based enterprise. The ground floor of the plot is a large room that is used exclusively to house buffaloes. The milkman himself resides with his family on the upper floors of the same built-up plot.<sup>6</sup> Although milkmen possess a license to practice dairy farming, their day-to-day operations bear the semblance of an informal sector – cash-based transactions, non-payment of taxes, no mechanization, and basic investment in infrastructure. Individual milkmen level surveys show that over 90 percent of the buffaloes are of the same breed.

Milkmen specialize in selling fresh buffalo milk, which differs from cow milk in having higher fat, protein, and solids-not-fat (SNF) content and is thus much more nutritious (Menard et al 2010). Milkmen do not compete with the formal sector, as the latter mostly sells cow milk. The competition between neighborhoods is also negligible because of large

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<sup>6</sup> We did not come across any milkman having plots across the neighborhoods. The room where the buffaloes are kept is usually dark, poorly ventilated, and smells strongly of animal waste.

distances, averaging 12 km, separating them. The market for fresh buffalo milk in Delhi is therefore a niche market and each neighborhood functions almost like a monopoly. Within neighborhoods, most milkmen collude on price and also raise it collectively once a year. As a result, the variation in price is very small.

Milkmen sell fresh buffalo milk directly to their customers, without any intermediaries. This allows us to map tightly the association between a milkman's dishonesty and water added to milk. The milk is sold twice a day, early in the morning and in the evening, mostly at the dairy. Customers are local households living within the five-kilometer radius of the dairy neighborhood. They line up outside the dairy and typically buy 1-2 liters of milk per day (Figure 2). While milkmen's customer base primarily comprises repeat customers, they also serve occasional customers.

Milkmen lack modern forms of production technology that permit differential provision of quality on the basis of the duration of repeated interaction. After milking buffaloes, the entire milk is pooled in a container from which it is then sold at the same price to customers waiting at the dairy (Figure 2). All customers are therefore sold the same milk quality and are even charged the same price regardless of the duration of repeated interaction. Furthermore, milkmen do not invest into branding or advertisements; none of the dairies even has a name. Investments in infrastructure or management practices that could allow for product differentiation along the lines of proper milk hygiene, waste management, and animal welfare are also lacking. These features limit the scope of reputation in mitigating cheating.

### *B. Milk quality in informal markets*

Milk markets are prone to product quality uncertainty. Milkmen milk buffaloes privately, in the absence of both customers and fellow milkmen, within the four walls of their dairy. Importantly, inferring quality by comparing the actual volume of milk sold to the predicted volume based on the size of buffalo herd is of limited guide. This is because the actual volume of milk sold depends on the number of lactating buffaloes, which is private information that is not accessible to customers and other fellow milkmen.<sup>7</sup> These features

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<sup>7</sup> Our survey data reveals that buffaloes lactate for a period of nine months in a year after which the milk dries up. During the lactation phase, buffaloes yield 9-10 liters of milk per day.

make ex-ante detection of milk quality challenging.<sup>8</sup> Similarly, ex-post detection of milk quality is also impeded. Professional laboratory testing of milk in Delhi costs at least USD 25 per sample and is largely restricted to industrial orders. In addition, the laboratories are located far from the neighborhoods where milkmen and their customers reside. Thus professional testing of milk is beyond the reach of customers. While simple milk testing procedures are available, as we show later, these are unreliable.

Under the existing law, there is a six months jail and /or a fine of INR 1,000 for selling adulterated milk, but monitoring and prosecution are rare. It is therefore not surprising that adulteration is rife. According to the national survey conducted by FSSAI (2011), 68 percent of the 1796 milk samples from India and 70 percent of the 71 samples from Delhi tested positive for adulteration. The most common adulterant was added water.

The practice of adding water is not an implicit arrangement between milkmen and their customers to provide a lower-quality product in exchange for a more affordable price. The buffalo milk in informal markets costs on average INR 57 per liter, which is much higher than the price of buffalo milk sold in the formal market (INR 50).<sup>9</sup> In a household survey, the milkmen emphatically stated that their customers demand pure, unadulterated buffalo milk and denied adding any water to milk. Many milkmen stated further that if customers wanted diluted milk they could add water themselves.

### *C. Milk quality and human health*

Adding water is more than just a simple redistribution of resources. Rather, dilution of milk with water reduces the nutritional value of milk (FSSAI 2011, FAO 2013, Handford et al. 2016). This is alarming because milk and milk products not only constitute up to 7 percent of the consumer expenditure in India, but also account for 13 percent of the total protein intake (Varadharajan et al. 2013). Our data also shows a fall in protein and nutrient (minerals and vitamins) content of milk due to the addition of water (see Section IV.B). If added water is contaminated, it additionally exposes consumers to health problems. The water that milkmen

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<sup>8</sup> After several rounds of surveys, a few milkmen confided in us and even showed us how and when they add water to milk. Water is either added ex-ante to the bucket in which the buffalo is milked or ex-post to the bucket full of milk.

<sup>9</sup> Buffalo milk was introduced only recently in the formal market (2013 onwards). As of now, only two brands are available. The formal market is predominantly based on cow milk.

add to milk is sourced from the ground and is contaminated with high nitrate content, especially in areas where the dairy neighborhoods are located (CGWB 2013).<sup>10</sup> Exposure to such contamination can lead to delayed health effects.

### III. Data Collection

We collect data using four different sources: milk purchase via assistants to assess cheating in milk markets, a behavioral experiment to measure norms of honesty, a milk-testing tournament to assess the scope of reputation, and one round of community and three rounds of household surveys to collect data on market structure and milkmen specific characteristics. The behavioral experiment was conducted in November 2014, milk samples were purchased a month later in December 2014, and the tournament was conducted in March 2015. The community and household surveys were implemented during in this period.

#### *A. Data on cheating in milk markets*

Assessing the extent of cheating in milk markets is not straightforward, as milkmen may add besides water a variety of other adulterants. Therefore, measures relying exclusively on added water may systematically understate the extent of cheating for some milkmen. Accordingly, we first verified in a pilot study that added water is the only adulterant. We purchased a liter of milk from 15-20 milkmen from each of the six neighborhoods and then split the sample into two parts. One part was tested for a variety of adulterants including water by a professional food-testing laboratory and the other part was tested for added water using an ultrasonic milk analyzer (see details in Appendix A.I). Besides confirming that added water is the only adulterant, the laboratory results on added water are strongly correlated with machine results ( $r = 0.93$ ). Accordingly, we use added water in milk as our measure of cheating in informal milk markets.

Assessing added water in milk at the individual level and then matching this with dishonesty in the behavioral experiment requires locating milkman. This is a daunting task because individual dairies typically do not have plot numbers or other identifiers, such as the

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<sup>10</sup> The CGWB (2013) report further states that water supplied by the Delhi Jal Board, which caters to a large fraction of Delhi, is not contaminated. Disentangling health effects from the consumption of contaminated milk could be very difficult, as in a place like Delhi there could be many other drivers of ill health.

name of the dairy. Therefore, we started by preparing detailed maps listing each milkman within a neighborhood and marked carefully the ones who took part in the experiment, as well as the ones who did not (Figure A1, Appendix A.I shows such a map for one neighborhood in our study).

We then let assistants unknown to the milkmen buy a liter of milk in a one-shot interaction from milkman who did and who did not take part in the experiment. Because milkmen did not know that the same team is behind both the behavioral experiment and milk purchase, they could not alter the milk quality sold to our assistants. Also, the milk samples were collected a month after the behavioral experiment was conducted. The assistants also noted the price at which the milk was purchased. All milk samples from within a dairy were obtained on the same day.

The milk samples were then tested for added water via an ultrasonic milk analyzer, which uses the freezing point of buffalo milk to calculate the percentage of added water in a liter of milk. The freezing point of milk is a biological constant that lies below the freezing point of water. However, as more water is added to milk, its freezing point moves closer to that of water (Advanced Instruments 1995).<sup>11</sup> Figure 3 shows the distribution of added water in milk. On average, 17.96 percent (s.d. 7.49) or 180 ml of every liter of milk sold by milkmen is actually water. We observe large variation in this outcome, ranging from as low as 4 percent to as high as 37 percent.

We ensure that this variation in milk quality is not capturing natural variation of water in milk. This is because unlike other milk ingredients that vary with the feeding and health status of an animal, the freezing point of milk remains fairly constant and is very difficult to tamper with (Buetler et al. 2008). Moreover, the variation in milk quality cannot be due to livestock variety either. Data on buffalo breed collected via household surveys shows that regardless of the neighborhood over 90 percent of the milkmen own the same buffalo breed. Note that because we collected milk samples from each neighborhood in the third week of December, weather fluctuations are unlikely to explain this variation. The variation in milk

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<sup>11</sup> The correct calibration of the base freezing point is crucial to obtain reliable measures of added water in milk. The producer of the machine, Milkotronic Ltd., maintains a large database on buffalo milk in India and calibrated the base freezing point accordingly. For more details, see [http://www.milkotronic.com/pdfs/Lactoscan\\_SA\\_Eng.pdf](http://www.milkotronic.com/pdfs/Lactoscan_SA_Eng.pdf).

quality is also not due to fluctuations in demand and supply, as data from household and community surveys suggest such fluctuations to be very rare.

We check the representativeness of our sample by buying milk from 63 milkmen from across the neighborhoods who did not take part in the experiment. We find no difference in added water ( $p$ -value = 0.41) as well as the price of milk ( $p$ -value = 0.66) between these and the milkmen in our sample (see Appendix A.II).

Lastly, we also collected a second round of milk sample for nearly half of the milkmen in our sample. There is a strong positive correlation between added water in the first and the second sample, which remains robust even when we control for neighborhood fixed effects ( $p$ -value = 0.016).

### *B. Milk testing tournament*

For reputation-based mechanisms to work, customers need a faint signal on observable aspects of milk quality, such as the extent of added water (Levin 2003, Board and Meyer-ter-Vehn 2013, Baker and Choi 2016, Ganuza et al. 2016). Because professional laboratory tests are costly for customers in this market, the signal is likely to be based on simple tests, which can be implemented at home.

To examine the scope of such signals, we conducted an incentivized milk-testing tournament with milkmen. The latter were chosen because they produce, dilute, sell and consume milk every day. Also, milkmen have the experience of handling pure milk and thus are likely to know its texture, density, and taste. For the tournament, we bought pure buffalo milk and then created five different milk samples by adding varying levels of water ourselves. We then asked milkmen to predict the amount of added water in each sample. Milkmen could taste the samples and test its viscosity by letting milk flow down their palm or fingertips. The tournament was conducted with milkmen from three neighborhoods. The three milkmen in each neighborhood whose predictions were closest to the actual level of added water were paid INR 800, INR 500, and INR 300 respectively. These earnings are worth 14, 9 and 5 liters of milk sold. Given that a buffalo yields 9-10 liters of milk per day, these incentives were high enough for milkmen to take the tournament seriously. This also

seems to be the case, as each milkman spent on average 4-5 minutes to predict added water in each sample.

Two variants of the tournament were implemented. In two dairy neighborhoods, milkmen were presented five different samples containing 0, 100, 200, 300 and 400 ml of added water. In the third dairy neighborhood, though the number of samples was also five, we presented two samples containing 250 ml, another two containing 350 ml, and finally the last sample containing 400 ml water. This variation allows us to test the accuracy in the level of predicted water within a milkman in samples that contain the same level of water.

### *C. Behavioral experiment to measure norms of honesty*

Measuring norms of honesty in the field is challenging because of potential confounds arising from opportunities for repeated interaction and reputation formation. Behavioral experiments allow researchers to exert control over these factors and obtain cleaner measures.

Our experimental strategy builds on games of chance, which involve self-reporting of outcomes of random events.<sup>12</sup> Individuals have to roll a die or flip a coin in private and then self-report its outcome. The payoffs depend entirely on the self-reported outcomes, providing individuals an incentive to report dishonestly by inflating the actual outcome. As there are no material gains from honest reporting in the game, any deviation from dishonesty is interpreted as reflecting norms of honesty (Fischbacher and Föllmi-Heusi 2013). Though the game is simple and easy to implement, measuring dishonesty is nonetheless challenging. Because the experimenter does not observe the actual outcome of random events, dishonest reporting can only be inferred at the group level by comparing self-reported outcomes with the corresponding theoretical probability distribution of the random events (Fischbacher and Föllmi-Heusi 2013). Hanna and Wang (2015) adapt this experimental strategy to measure dishonesty at the individual level by allowing for a sufficiently large number of repetitions of the random task by the same individual.<sup>13</sup> Using this adaption, an individual's self-reported

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<sup>12</sup> Rosenbaum et al. (2014) provide an overview of other experimental designs to measure dishonesty.

<sup>13</sup> Hanna and Wang (2015) compute the necessary number of repetitions to be 37 to achieve a power of 80 percent at a significance level of 5-percent based on the (implicit) assumption that an individuals' reporting behavior in each roll is an independent draw from the aggregate reporting behavior observed in the study by Fischbacher and Föllmi-Heusi (2013).



outcomes can be used to assess dishonesty via a binary classification – individuals whose sum of self-reported outcomes falls below the critical threshold at the chosen level of significance (typically 1-percent) are classified as “honest” and the remaining as “dishonest”.

However, such a simple dichotomy of types may not fully capture the heterogeneity in dishonesty, as individuals might differ not only with respect to the incidence of dishonesty, but also in its extent. For example, laboratory studies find that even when participants cheat they refrain from cheating maximally (Mazar et al. 2008, Fischbacher and Föllmi-Heusi 2013, Pruckner and Sausgruber 2013). Thus, when relying only on the binary measure, one may miss important information - the degree of dishonesty. While in principle one could use the distance of the reported number of points from the critical threshold as a proxy for the degree of dishonesty, such a measure would be coarse and imprecise due to the randomness of the underlying task.

Another concern with the binary measure is its potential susceptibility to measurement error. Whereas some individuals might be erroneously classified as ‘dishonest’ because their self-reported outcomes surpass the critical threshold by pure chance, others might be classified as ‘honest’ despite severe over-reporting, if the self-reported outcome falls below the critical threshold. Though these errors can be somewhat mitigated by increasing the level of significance and the number of die rolls, finding the appropriate number of repetitions per individual is difficult due to both statistical and pragmatic reasons. On the one hand, one has to correctly forecast the effect size, i.e. the degree of over-reporting for a given number of repetitions. On the other hand, one has to consider issues related to the implementation of the experiment (e.g. amount of time, fatigue, and tediousness of the task, which increase with the number of repetitions). As we show in Section IV.D. the binary measure is indeed prone to measurement errors.

*Experimental design.*– Given that the binary measure is unable to capture degrees of dishonesty and is also prone to measurement errors, a continuous measure in which these concerns are alleviated is warranted. We achieve this by appending the die-roll task with a novel technology. We conducted the experiment with a Bluetooth enabled die, which transmits the actual outcome of each roll to the hidden smartphone of one of the authors. We then compare self-reported outcomes of the die rolls with the actual outcomes rolled by each

individual milkman. This feature not only allows us to identify dishonest milkmen, but also to assess precisely their degree of dishonesty.<sup>14</sup>

In the experiment, milkmen have to roll a six-sided die 40 times and report the outcome of each roll by striking out the appropriate number of 2 Indian Rupee (INR) coins on a game sheet.<sup>15</sup> For every coin struck on the game sheet, a milkman is paid INR 2. Earnings in the game thus range from INR 80 (reporting all 1's) to INR 480 (reporting all 6's) and increase linearly in the number of reported points. This provides milkmen an incentive to over-report. Instructions were neutral and did not encourage dishonesty but explicitly stated to roll the die and report the number (Appendix B). The responses in the post-game survey confirm that milkmen were aware of the possibility to increase their payoffs by over-reporting the actual outcomes.

While conducting the experiment, we took great care to ensure that every milkman understood the game, carried out the experiment as outlined (e.g. rolled the die) and that contagion across participants was minimized. The experiments were conducted within the neighborhood where the milkmen reside. After all milkmen took part in the experiment, they were invited to fill a post-game survey in private. Upon the completion of the survey, milkmen were paid their earnings from the experiment. On average, milkmen earned INR 495 (USD 8) including a show-up fee of INR 200.

*Measures of dishonesty.*— In line with the literature, we interpret honest reporting in the experiment as reflecting norms of honesty, as there are no material or other strategic gains from doing so. 36 out of 72 milkmen in our sample (50 percent) cheated by self-reporting higher than the actual outcome. We develop different measures, which differ in their informational content and their sensitivity to the randomness of the die-roll task. The simplest measure, *number of over-reported rolls*, treats the outcome of each die roll as a binary event and counts over all die rolls the number of times the self-reported outcome exceeds the actual outcome. A related measure additionally considers the magnitude of over-

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<sup>14</sup> To show that our measures are not affected by the use of a Bluetooth die itself, we also conducted a control experiment in which half of the participants played the game with a Bluetooth die and the other half with a standard die that can be purchased in local markets. We find that there is no difference in the reporting behavior across the two groups of participants (see Appendix A.III).

<sup>15</sup> We opted for this particular reporting scheme to make payoffs more salient given that the pool of participants had no prior experience in economic experiments.

reporting by using the *sum of added points* over all die rolls.<sup>16</sup> Panel B of Table 1 reports summary statistics on these measures. On average, milkmen over-reported in 3.6 rolls by nearly 7.5 points.

*Correlates of dishonesty.*— In Table A2 in Appendix A.IV we examine the correlates of dishonesty. In column 1, we include milkmen specific characteristics, followed by livestock specific characteristics in column 2 and neighborhood fixed effects in column 3. Regardless of the specification, we find that dishonesty is uncorrelated with control variables.

#### D. Community and household survey

We collected data using three rounds of community and household surveys. These surveys covered a variety of questions ranging from socio-demographic and livestock related input factors to organization of milk markets, pricing of milk, fluctuations in supply and demand, milk quality demanded and supplied, customer base, buffalo breeds, and perception of the behavioral experiment used to measure norms of honesty.

#### E. Sample construction

Our sample comprises milkmen from five of the ten dairy neighborhoods of Delhi and a sixth one from an adjoining city in Uttar Pradesh. We exclude three dairy neighborhoods because these contain only large milkmen, where laborers rather than milkmen themselves are involved in dairy operations. Another two dairy neighborhoods were unviable for the study because of their small size. Our baseline survey and detailed maps suggest that these six neighborhoods comprise largely of small milkmen, numbering roughly 160. Of these, 74 milkmen from three neighborhoods took part in the milk testing tournament and 72 milkmen from six neighborhoods in the behavioral experiment.<sup>17</sup>

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<sup>16</sup> While the number of points an individual can add in a single die roll always depends on its actual outcome, the decision whether to over-report or not is only restricted by the actual outcome, when a ‘6’ is realized. When the actual outcome is a ‘1’, a milkman can add 0, 1, 2, 3, 4, or 5 points, but he can only add up to two points for a ‘4’ and cannot add any points when the actual outcome is a ‘6’.

<sup>17</sup> Actually 84 milkmen took part in the behavioral experiment. We could not locate nine milkmen to obtain the field outcome and for another three milkmen the information from the Bluetooth die is missing. Excluding these 12 observations leaves us with a final sample of 72 milkmen. We verify that these 12 milkmen do not differ from the rest in their self-reported outcomes in the experiment or their socio-demographic characteristics (see

## IV. RESULTS

We first present results on the scope of reputation in explaining the variation in cheating in milk markets, followed by results on the role of norms of honesty. Finally, we discuss the role of market power in allowing for the coexistence of honest and dishonest types.

### *A. Reputation and cheating in milk markets*

We offer evidence from the milk-testing tournament, which together with specific features of our field setting can be interpreted as reflecting a limited scope of reputation in explaining the variation in cheating in informal milk markets.

*RESULT 1: In the milk-testing tournament, milkmen are unable to distinguish different qualities of milk, including samples in the extreme range, such as pure milk from highly diluted milk.*

Figure 4a and 4b and Table 2 provide support for this result. Figure 4a shows boxplots of predicted level of water reported by milkmen for each level of actual water in milk samples. Two patterns are noteworthy. First, milkmen are clearly unable to distinguish different qualities of milk. The predicted level of water actually shows a wave like pattern with respect to the increasing level of actual level of added water in milk. Milkmen perceive samples containing 0, 200, 300 and 350 ml of added water as most diluted, whereas samples containing 100, 250, and 400 ml of added water are perceived as least diluted. Remarkably, for the pure milk sample containing zero level of added water, the median prediction is 137.5 ml of added water. In contrast, for the most diluted sample containing 400 ml of added water, the median prediction is even lower at 100 ml of water. A test based on median regression suggests that regardless of the actual level of added water in milk, the median predictions are not significantly different from each other ( $p$ -value = 0.25). Second, the variance in predicted

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Table A1, Appendix A.II). It was not possible to include all milkmen in our study. The use of the Bluetooth die meant that every milkman required our personal attention. Therefore, we could not run the experiment with multiple milkmen at the same time, as would have been possible with a normal die. Also, milkmen have limited free time within which we had to accommodate our study. This together with our strategy of conducting the behavioral experiment within a neighborhood on a single day to prevent contagion restricted the sample size further. In the experimental pilot studies that we conducted, a session with 15 participants lasted up to three hours including the post-experimental survey and payments.

level is expected to be smaller for pure and most diluted samples but larger for the intermediate values. However, as Figure 4a clearly shows the interquartile range is fairly similar across the actual levels. Results from a robust variance test confirm this; the null hypothesis that the variance is similar across different qualities of milk cannot be rejected ( $p$ -value  $> 0.74$ ).

In Table 2, we test econometrically for the association between predicted and actual amount of added water in milk, clustering standard errors on the individual. Column 1 is without controls and shows that the coefficient on the actual level of added water not only has the negative sign but it is also close to zero in magnitude and is statistically insignificant (-0.016, s.e. 0.058). The introduction of individual fixed effects in column 2 leads to fall in the absolute magnitude of the coefficient and it remains negative and statistically insignificant (-0.005, s.e. 0.06).

As a further confirmatory test, in Figure 4b we compare predicted levels of water in milk across samples containing the same actual level of added water. As described in Section III.B, in one of the dairy neighborhoods, we presented milkmen two samples containing 250 ml water and another two samples containing 350 ml water. As before, milkmen are not only unable to distinguish different qualities of milk, but even incorrectly predict the same quality as having different levels of water. For instance, when the actual level of water in milk is 250 ml, the median predictions are 150 ml in the first sample and 100 ml in the second sample; these differences are even statistically significant ( $p$ -value 0.03). Similarly, when the actual level of water is 350 ml, the median predictions are 125 ml for the first sample and 175 for the second sample, although these differences are not significantly different from each other.

One concern could be that because milkmen cheat while selling milk, they are also cheating by deceiving us in the milk-testing tournament. We believe this to be unlikely because the tournament had high financial stakes and the winners earned amounts worth 14, 9 and 5 liters of milk sold in the market. Also, if milkmen are indeed deceiving us then we should observe that the difference in predicted and actual water is stronger in neighborhoods where milkmen cheat more on average. Our results in Figure A2 in Appendix A show that though the neighborhoods differ significantly in their cheating behavior, this has no bearing on how far or near the predicted values are from the actual value of added water in the tournament. A regression-based test in Table A3 of Appendix A.V, whereby we also control

for the actual level of water in milk, further confirms these results. Third, for milkmen from one neighborhood, we have data on both water added to milk and predicted value in the tournament. Our results, which are reported in Table A4 in Appendix A.V, again show that there is no association between the two. These results set serious doubts that milkmen were deceiving us in the tournament.

Taken together, these findings suggest that it is very difficult to get even a weak signal on milk quality that is necessary for reputation-based mechanisms to work. In combination with our field setting whereby milkmen supply the same quality to all their customers regardless of the duration of repeated interaction, these findings can be interpreted as reflecting a limited scope of reputation in mitigating cheating in informal milk markets.

### B. Dishonesty and cheating in milk markets

We now investigate the scope of norms of honesty in explaining the variation in cheating in milk markets using the following OLS specification:

$$y_{in} = \beta_0 + \beta_1 \text{Dishonesty}_{in} + \beta_2 \text{Price}_{in} + \beta_3 \mathbf{X}_{in} + \beta_4 \mathbf{L}_{in} + \alpha_t + \alpha_n + \alpha_a + \varepsilon_{in},$$

where  $y_{in}$  is the percentage of water added by milkmen  $i$  from neighborhood  $n$  in a liter of milk sold in the market.  $\text{Price}$  is the amount charged by a milkman for a liter of milk.  $\mathbf{X}$  is a vector of milkmen specific factors including age, education, religiosity, and caste dummy.  $\mathbf{L}$  is a vector of livestock specific factors, such as buffalo herd size and lactation period.  $\alpha_t$ ,  $\alpha_n$ , and  $\alpha_a$  are fixed effects for the time of the day the milk sample was purchased, the neighborhood where a milkman resides, and the assistant who bought the milk.  $\varepsilon_{in}$  is an in error term. The variable *Dishonesty* captures the effect of degree of dishonesty on cheating in milk markets, measured as the number of over-reported rolls. Subsequently, we also present results using the binary measure of dishonesty. Given our hypothesis, we expect  $\beta_1$  to be positive, that is, cheating in milk markets increases with the degree of dishonesty.

**RESULT 2:** *There is a strong positive association between the degree of dishonesty and the amount of water added to milk, which is significant at the 1-percent level.*

Table 3 presents results on the association between the degree of dishonesty and cheating in milk markets. Column 1 is without any additional controls and shows that dishonesty has a positive coefficient (0.291, s.e. 0.158), which is significant at the 10-percent level. This implies that the amount of added water to milk sold in the market increases with the milkmen's degree of dishonesty. We are worried that this association might be capturing differences in neighborhood specific factors, so we introduce in column 2 fixed effects for the neighborhood where a milkman resides. The coefficient on dishonesty rises slightly to 0.324 (s.e. 0.150), but its standard error declines, such that it is now significant at the 5-percent level. The fixed effects for neighborhood are jointly statistically significant at the 1-percent level.

To ensure that our results are not capturing the effect of other factors that vary within a neighborhood, we include proxies for price, milkmen specific socio-demographic variables, inputs to milk production, and fixed effects for the time of the day the milk sample was bought and assistants who bought milk in column 3 (Armantier and Boly 2011, Balafoutas et al. 2013). The coefficient on dishonesty rises to 0.464 (s.e. 0.140) and is now significant at the 1-percent level. This means that milkmen add, on average, 0.46 percentage points more water to milk per over-reported roll. Put differently, one standard deviation increase in the number of over-reported rolls (6.60) is associated with a rise in added water in milk by 3.06 percentage points, which is one-sixth of the mean level of added water.

Among the covariates, the coefficient on price is small in magnitude and remains statistically insignificant throughout. In contrast, the dummy for the caste is positive and significant at the 5-percent level, suggesting that milkmen from pastoral caste groups add more water to milk than milkmen from other caste groups. The coefficient on religiosity is negative and significant at the 5-percent level, suggesting that more religious people add less water to milk. The dummy for the lactation period is negative and statistically significant at the 1-percent level. This is expected because during the first half of the lactation period (roughly three months) the buffalo milk contains less fat and is less dense (FAO 2013), which could discourage milkmen from adding further water to milk. The control variables are powerful predictors of cheating in milk markets, as their inclusion leads to a jump in the R-squared from 0.24 in column 2 to 0.55 in column 3. Nonetheless, dishonesty explains the largest variation in cheating in milk markets (21 percent).

These results hold when we account for the potential spatial correlation of errors by clustering at the neighborhood level using wild bootstrap procedures to account for the small number of clusters (Cameron et al. 2008). The coefficients on dishonesty, caste, religiosity, and lactation retain their significance, while that on price remains statistically insignificant.

Our results also hold when we use added water in the second sample of milk that we collected for a sub-set of milkmen in our sample. For 29 such milkmen, we also have the measure of dishonesty. We find that the coefficient on dishonesty in this sample is 0.599 (s.e. 0.103), which is statistically significant at the 1-percent level and slightly larger than what we observe in the full sample.<sup>18</sup>

Columns 4 and 5 further show that the association between cheating in milk markets and dishonesty is robust to the exclusion of influential individual observations. Regardless of whether we drop one or four influential observations, the magnitude of the coefficients on dishonesty, caste, religiosity, and lactation remain stable in magnitude and statistical significance.<sup>19</sup> In contrast, the coefficient on price declines in magnitude by almost half and remains statistically insignificant. As mentioned before, our results are unlikely to be reflecting differences in weather condition and variation in buffalo breed. Together, these findings point towards an important role of dishonesty in predicting cheating in milk markets.

Our estimates are also economically relevant. The water that is added to milk is sourced from the ground and is thus for free. This means an increase in adulteration of milk associated with a one-standard deviation increase in the number of over-reported rolls would yield milkmen higher profits on average by INR 3. Over the course of a month, depending on the size of the dairy and the cheating behavior of a milkman, the additional gains correspond to up to 8 percent of a milkman's monthly income.<sup>20</sup> Together, these results highlight an

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<sup>18</sup> We show that milkmen for whom we have the second sample do not differ in socio-economic characteristics from milkmen for whom we do not have the second sample in Table A5, Appendix VI.

<sup>19</sup> Influential observations are identified using DFITS, which classifies observations as influential, if the difference in fitted values with and without the  $i$ -th observation is larger than  $2 \cdot \sqrt{k/N}$ , where  $k$  is the number of parameters and  $N$  is the sample size.

<sup>20</sup> To compute additional profits from adding water, we calculate additional revenue earned by selling a liter of pure buffalo milk by increasing the level of added water in a liter of milk sold by 3 percentage points. We therefore divide the price charged for one liter of milk by a given milkman by its share of pure milk (1 - added water in percent) and compare this to the quotient of the price and its share of pure milk minus the additional 3 percentage points. To compute the monthly profit, we use the average number of lactating buffaloes (13.20) and assume an average milk yield per buffalo per day of 10 liters, which is based on data obtained from the household survey.



important role of norms of honesty in mitigating cheating in informal milk markets.

RESULT 3: *Adulteration of milk with water reduces significantly the nutrient quality of milk, as measured by protein and solids not fat (SNF) content.*

Table 3 provides support for result 3. Though it is beyond the scope of this study to show the negative consequences of dishonesty on human health and nutrition via the addition of water to milk, we highlight its negative association with the amount of protein (column 6) and micronutrients (SNF) in milk (column 7). A one-standard deviation increase in the number of over-reported rolls (6.6) leads to a fall in protein content of milk by 0.20 percentage points and in SNF by 0.43 percentage points. Given that the average levels of these nutrients in buffalo milk are 7.21 and 3.25 percent, these losses are not trivial.

### *C. Robustness checks*

We present results from a number of robustness tests, which corroborate our findings on the importance of norms of honesty for cheating in milk markets.

RESULT 4: *The association of norms of honesty with cheating in milk markets is robust to alternative measures of dishonesty, dropping neighborhoods, and additional controls. These findings suggest that our results are not being driven by omitted variables.*

We first reproduce our results using alternative measures. We start with the sum of added points, which allows us to go beyond the incidence and take the magnitude of over-reporting into consideration. Column 1 in Table 4 reports the result and shows that the coefficient is 0.166, which is significant at the 1-percent level. According to this estimate, one standard deviation increase in the sum of added points (15.85) leads to an increase in added water by 2.63 percentage points. Our measures of dishonesty thus far could be partly reflecting ‘bad luck’ in the experiment. To mitigate this, we construct two additional measures, which express the number of over-reported rolls and the sum of added points in relative terms. We construct the *share of over-reported rolls* by dividing the number of over-reported rolls by the number of recorded rolls in which an individual did not obtain a ‘6’, as

in this case over reporting is not possible. Similarly, for the *share of added points*, we calculate the ratio between the sum of added points and the maximum number of points a milkman could have added given his realizations in the recorded die rolls. Columns 2-3 in Table 4 report the results and show that the association of these two measures of dishonesty with cheating in milk markets remains positive and highly statistically significant ( $p$ -value < 0.001). Notably, standardized coefficients show that estimates obtained from different measures are comparable to each other and fall between 2.6 and 3.1.

We next proceed to show in Table 5 that our results are not due to a specific neighborhood. Columns 1-6 show changes in the coefficient on the dishonesty variable resulting from dropping one neighborhood at a time. Overall, the coefficient on dishonesty remains robust in both magnitude and significance. It is over 0.40 in magnitude in all except column 5, where it drops to 0.33, but remains significant at the 5-percent level.

We also test the robustness of our results to the inclusion of additional control variables, the results of which are reported in Table 6. We begin by addressing the concern that milkmen add varying quantities of water to increase their total output because of differences in the quality of fodder fed to the buffaloes. Although this is still cheating, we nonetheless control for fodder quality using the milkmen's monthly expenditure on fodder, as reported in the household survey (column 1). We account for the importance of the home environment as a predictor of dishonest behavior using a dummy variable for the state of origin of the milkman (column 2). Furthermore, milkmen might vary in their cheating behavior due to differences in outside options (column 3). Due to the difficulty involved in obtaining this data, we use a dummy variable, which takes the value of 1 if a milkman or his family members have a job outside the dairy sector, and 0 otherwise. Another important factor behind differences in cheating could be family size because milkmen with larger families have higher living expenses (column 4). We use duration of stay within a dairy to account for learning effects regarding returns from cheating (column 5). A milkman might cheat because his neighbors also cheat. We test this by including the number of over-reported rolls of the nearest neighbor as an additional control (column 6). Finally, we also additionally test for the role of luck by explicitly including the actual outcome of the die rolls as an additional regressor (column 7). The results clearly show that the coefficients on additional control variables are statistically insignificant. In contrast, the coefficient on dishonesty

remains remarkably stable in magnitude (around 0.46) and significance ( $p$ -value  $< 0.001$ ). Introducing controls for exact time (in hours) at which the sample was bought and the temperature of milk at the time when it was tested also have no bearing on our findings and they remain unchanged (results not reported).

Due to temporary connectivity deficiencies, the Bluetooth die did not transmit the actual outcome for nearly 10 percent of the die rolls. We refer to such rolls as ‘missed rolls’. While our continuous measures of dishonesty account for this, we nonetheless conduct a battery of robustness checks to show that this has no implication for our results, which are reported in Table A6, Appendix A.VII. The coefficient on the number of over-reported rolls is close to 0.46 and remains significant at the 1-percent level. All of these results also hold when we use alternative measures of dishonesty.

#### *D. Results using the binary measure*

We also consider a binary measure to assess whether the Bluetooth-based information is actually warranted. It is based on the number of self-reported points that a milkman is sufficiently unlikely to accumulate over 40 die rolls. Using a normal distribution and the critical threshold at the 1-percent level of significance, this turns out to be 166 points. We classify all those milkmen as ‘dishonest’ whose self-reported points fall above this threshold, and the remaining as ‘honest’. Under the binary measure, only nine milkmen (12.5 percent) are classified as dishonest. Hence, 27 out of the 36 milkmen who are actually dishonest in the experiment are misclassified as honest by this binary measure, resulting in a Type-II-Error of 37.5 percent.<sup>21</sup>

*RESULT 5: The binary measure is prone to sizable measurement errors arising from the misclassification of weakly dishonest milkmen as honest. Though the binary measure of dishonesty is also positively and significantly associated with added water to milk, the association turns out to be downward biased by 15-20 percent.*

Table 7 provides support for the result. The binary measure misclassifies 27 milkmen

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<sup>21</sup> The measurement error does not disappear but rather increases when we use the critical threshold at the 5-percent level of significance to identify dishonest milkmen.

as honest, but as column 1 shows these milkmen are actually dishonest. They over-report by 3.8 points more than the milkmen who report honesty in all their rolls and this difference is highly significant ( $p$ -value  $< 0.001$ ).

Column 2 shows the association between norms of honesty as measured using the binary measure and cheating in milk markets. Despite the sizable Type-II-Error, the coefficient on the binary measure of dishonesty is positive and highly significant. Dishonest milkmen add, on average, 7.8 percentage points more water to milk than honest milkmen. However, when we correctly assign the 27 misclassified milkmen to their own category ‘weakly dishonest’, the coefficient on the dishonesty dummy representing the nine ‘strongly dishonest’ milkmen rises from 7.815 (column 2) to 9.407 (column 3) and remains significant at the 1-percent level. Further analysis shows that these two estimates are significantly different from each other ( $p$ -value = 0.019). These results suggest that estimates obtained using the binary measure are downward biased by 17 percent. The bias actually rises to 20 percent when we use the 5-percent level of significance as the critical threshold to construct the binary measure. In this case, the biased and unbiased coefficients are 5.905 (s.e. 2.005) and 7.377 (s.e. 2.162); they are also significantly different from each other ( $p$ -value = 0.031). Note that the coefficient on the ‘weakly dishonest’ milkmen in column 3 while remaining positive is individually statistically significant at the 5-percent level. This suggests that the 27 dishonest milkmen who are misclassified as honest by the binary measure add nearly 3.3 percentage points more water to milk than honest milkmen.

Overall, these results suggest the relevance of the Bluetooth-based information. They also point towards the identification and measurement of weak cheaters in explaining cheating behavior.

#### *E. Market power*

The co-existence of honest and dishonest milkmen within a neighborhood is intriguing, as dishonest milkmen may drive out honest milkmen by setting the price of milk below the marginal cost of production by honest milkmen. However, during community interviews, we found that within a neighborhood most milkmen collude by fixing the price of milk and raising the price collectively by a fixed amount every year. Therefore one possibility could be that this collusion facilitates the co-existence of honest and dishonest milkmen by

allowing milkmen to earn joint monopoly profits.<sup>22</sup> However, because each milkman can earn an even higher profit by deviating from collusion, the plausibility of this argument rests on the stability of collusive arrangements. Drawing on the works of Grout and Sonderegger (2005), Harrington (2006), and White et al. (2013), we highlight several characteristics of milk markets that together with the field setting foster this stability.

*RESULT 6: Collusive agreements on price facilitate the co-existence of honest and dishonest milkman-types within the same market. Several market conditions facilitate the stability of these arrangements.*

For collusive arrangements to be self-enforcing, infinitely repeated interactions and strong punishment are needed to outweigh potential short-term gains from deviation. Because milkmen live and operate their dairy farms in neighborhoods that are stable in composition, it can be inferred that they are engaged in an infinitely repeated game. High densities of dairy farms and smaller number of milkmen within the neighborhoods (Figure 1) facilitate easy monitoring of deviations. In contrast to the milking of buffaloes that is done inside the dairy and is thus opaque, prices charged by milkmen can be ascertained by fellow milkmen from customers. Moreover, milkmen across the neighborhoods belong to tight-knit agro-pastoral ethnic groups, which make deviations socially costly, including exclusion from the group. In the community survey, milkmen indeed reported that they discourage customers to switch from one milkman to another within a neighborhood to avoid conflict.

The informal milk markets also fulfill many characteristics identified in the literature that are necessary for the stability of collusive agreements. The zoning laws in Delhi permit animal husbandry only in 10 neighborhoods located on the outskirts of the city. Because no new plots are available in these neighborhoods, it imposes high barriers to market entry, which are unlikely to change in the future. Another important feature is the stability of demand. From the community survey, we know that fluctuations in both demand and supply of milk are rare and occur at the most once a month. Likewise, the literature suggests that asymmetries in cost make collusion difficult. The marginal cost of producing milk, other than cost saving from the addition of water to milk, comprises mainly buffalo feeding costs.

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<sup>22</sup> Capacity constraint is unlikely to be the reason, as dishonest sellers can earn higher profits due to the addition of water to milk. They can expand by renting the plots of honest milkmen.

Milkmen buy buffalo feed in bulk, which is typically offloaded outside the dairy. Our data suggests little systematic variation in feeding costs across honest and dishonest milkmen. In a regression of buffalo feeding costs on a dummy variable for dishonest milkmen (built using data from the Bluetooth die), the coefficient is highly statistically insignificant, both without and with neighborhood fixed effects ( $p$ -value  $> 0.78$ ). Furthermore, the scope of deviation from collusion via other avenues is also unlikely, as milkmen sell only liquid milk and not milk products or ancillary services. Finally, in our setting customers buy mostly a liter or two of milk, which further ensures that buyer power is not able to break collusive agreements.

## **V. Conclusions**

Many developing economies are dominated by informal sector and weak enforcement of rules. Under these conditions, sellers are expected to cheat by replacing good quality with poor quality, especially when the product quality is difficult to ascertain. This is a serious concern, particularly when the market is for food products and public health is at stake. However, despite several incentives to cheat, a large and persistent variation is observed in the cheating behavior of sellers.

This paper measures and disentangles the importance norms of honesty in explaining this variation in a setting where reputation is unlikely to play a role. It also shows that for norms of honesty to matter, specific institutional environment may be needed and that market power offers one such environment. The setting is that of informal markets for buffalo milk in India, which are vital for health and nutrition. These markets, however, are prone to asymmetric information, poor enforcement of rules, and large variation in cheating in the form of addition of milk with mostly water.

We first confirm the limited role of reputation in explaining the variation in cheating. For reputation to work, customers need a weak signal on milk quality. We test empirically the scope of receiving such a signal via a milk-testing tournament. We present milkmen with several samples of milk containing different levels of water added by us and ask them to predict the same. Our results reveal that milkmen are unable to distinguish different qualities of milk. In fact, they perceive pure milk to be more adulterated than even the most adulterated sample. In addition, milkmen lack modern forms of organization that allow for product differentiation: all customers are sold the same quality of milk for the same price,

regardless of the duration of repeated interaction.

We proceed by examining the role of norms of honesty in explaining the large variation in cheating. For this purpose, we measure the dishonesty of milkmen via a behavioral experiment and combine this with milk purchased from the same milkmen. In the experiment, milkmen have to roll a die and then self-report its outcome. We complement this design using a Bluetooth enabled die, which additionally allows us to obtain actual outcomes of the die rolls. We contrast actual and self-reported outcomes to build continuous measures of dishonesty. This innovation allows us to capture the heterogeneity in dishonesty, which we document to be large. We then buy milk from the same milkmen in a one-shot interaction and test these for precise levels of added water using an ultrasonic milk analyzer.

We find a strong and significant association between dishonesty and added water in milk, which holds to a powerful set of controls including the price of the milk sample and fixed effects for the neighborhood where a milkman resides. Though our results also hold when we use only self-reported data to classify milkmen into honest and dishonest types, we show that these results are prone to large measurement errors, which biases downwards the effect by 15-20 percent. Finally, collusive agreements on price allow for the co-existence of honest and dishonest milkmen. Several market features facilitate the formation and stability of such agreements.

Our findings have important implications for optimal contracting and government policy. Heterogeneity in norms of honesty calls for a differentiated policy response. Policies based exclusively on self-interested sellers to counteract cheating, such as monitoring and punishment, might signal distrust and crowd-out the intrinsic motivation of honest sellers. Several laboratory and field studies have demonstrated causally the perverse effects of such incentives on intrinsic motivation (see Bowles and Polonia-Reyes 2012). For instance, in a famous study Mellström and Johannesson (2008) tested such a crowding out hypothesis postulated by Titmuss (1970) and found that putting a monetary value on a bottle of donated blood led to the erosion of intrinsic motivation to donate blood. In another study, Falk and Kosfeld (2006) show that agents display substantially lower trust when principals signal distrust by exerting ex ante control. Importantly, policies aimed at breaking collusive arrangements among milkmen might drive honest milkmen out of the market, resulting in even poorer market performance.

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Table 1: Summary Statistics

	Mean	Std. Dev.
<i>A. Cheating in milk markets</i>		
Added water to milk in percent	17.962	7.488
<i>B. Dishonesty measures</i>		
<i>Degree of dishonesty</i>		
Number of over-reported rolls	3.625	6.604
Sum of added points	7.486	15.851
Binary measure of dishonesty	0.128	0.331
<i>C. Control variables</i>		
Price	57.715	4.278
Age	33.847	11.089
High school	0.667	0.475
Caste	0.403	0.494
Religiosity	22.226	36.708
Buffalo herd size	18.778	35.619
Lactation period	0.792	0.409

*Notes.* Added water in milk is the percentage of water in a liter of buffalo milk purchased from the milkmen. Number of over-reported rolls is the number of rolls, in which the self-reported outcome exceeds the actual outcome. Sum of added points is the number of points added over all die rolls. Price is the amount paid for a liter of milk. Age is measured in years. High school is a dummy variable, which equals 1 if a milkman has high school education, otherwise 0. Caste is a dummy variable, which equals 1 if a milkman belongs to *Gujjar / Jat* caste groups, otherwise 0. Religiosity is the number of visits to a temple or a mosque in a month. Buffalo herd size is the number of adult buffaloes owned by a milkman. Lactation period is a dummy variable equal to 1, if any of the buffaloes were in the first three months of lactation period in December 2014, otherwise 0. Data on lactation period was not available for two milkmen and was consequently imputed. The mean of this variable without the imputed values is 0.79 (s.d. 0.41). All our results hold, if we drop these two observations. We do not separately control for religion as we have few Muslims, all from a single neighborhood. Our results remain robust even when we do this.

Table 2: Predicting Added Water in Milk in the Milk Testing Tournament

	Predicted Water Level	
	(1)	(2)
Actual Water Level	-0.016 (0.058)	-0.005 (0.060)
Constant	161.606*** (17.91)	158.959*** (14.966)
Individual fixed effect	No	Yes
Observations	370	370
Individuals	74	74

*Notes:* OLS regression with standard errors clustered on the individual in parentheses. \*\*\* Significant at the 1-percent level.

Table 3: Dishonesty and Cheating in Milk Markets

	Added Water in Milk in Percent					Protein	SNF
	No	Fixed	Full	Drop one	Drop four	Full	Full
	controls	effects	controls	influential obs.	influential obs.	controls	controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dishonesty	0.291*	0.324**	0.464***	0.394***	0.457***	-0.030***	-0.065***
	(0.158)	(0.150)	(0.140)	(0.138)	(0.127)	(0.009)	(0.019)
Price			-0.329	-0.213	-0.190	0.022	0.046
			(0.217)	(0.165)	(0.157)	(0.014)	(0.030)
Age			-0.054	-0.040	-0.023	0.004	0.008
			(0.065)	(0.065)	(0.066)	(0.004)	(0.009)
High school			-1.793	-1.471	-1.090	0.102	0.245
			(1.689)	(1.694)	(1.633)	(0.108)	(0.232)
Caste			3.978**	3.813**	3.774**	-0.279**	-0.568**
			(1.798)	(1.821)	(1.813)	(0.110)	(0.236)
Religiosity			-0.039**	-0.038**	-0.039**	0.002*	0.005*
			(0.019)	(0.018)	(0.019)	(0.001)	(0.002)
Buffalo herd size			0.013	0.014	-0.050	-0.001	-0.002
			(0.012)	(0.011)	(0.086)	(0.001)	(0.002)
Lactation period			-5.333***	-6.041***	-6.707***	0.334***	0.705**
			(1.902)	(1.793)	(1.722)	(0.125)	(0.270)
Neighborhood FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Time/ assistant FE	No	No	Yes	Yes	Yes	Yes	Yes
Constant	16.905***	14.442***	44.651***	37.888***	36.568***	1.489*	3.513*
	(0.944)	(1.969)	(13.262)	(9.957)	(9.532)	(0.840)	(1.837)
Observations	72	72	72	71	68	72	72
R-squared	0.07	0.24	0.55	0.57	0.62	0.55	0.54

Notes. OLS regression with robust standard errors in parentheses. FE stands for fixed effects. SNF stands for solids not fat. Protein and SNF are measured in percent. \*, \*\*, \*\*\* Significant at the 10-percent, 5-percent, and 1-percent level, respectively.

Table 4: Robustness Check: Alternative Measures of the Degree of Dishonesty

	Dependent variable: Added Water in Milk in Percent		
	Sum of added points (1)	Share of over-reported rolls (2)	Share of added points (3)
Dishonesty	0.166*** (0.062)	0.157*** (0.044)	0.159*** (0.046)
Price	-0.335 (0.235)	-0.333 (0.225)	-0.324 (0.228)
Age	-0.067 (0.066)	-0.054 (0.065)	-0.056 (0.066)
High school	-2.068 (1.669)	-1.778 (1.682)	-2.099 (1.664)
Caste	3.850** (1.797)	4.021** (1.789)	4.021** (1.800)
Religiosity	-0.036* (0.020)	-0.040** (0.019)	-0.037* (0.019)
Buffalo herd size	0.010 (0.012)	0.012 (0.012)	0.012 (0.012)
Lactation period	-5.156** (2.014)	-5.285*** (1.915)	-5.385*** (1.944)
Neighborhood FE	Yes	Yes	Yes
Time/ assistant FE	Yes	Yes	Yes
Constant	46.166*** (14.296)	44.834*** (13.772)	45.110*** (13.822)
Observations	72	72	72
R-squared	0.52	0.56	0.54

*Notes.* OLS regression with robust standard errors in parentheses. FE stands for fixed effects. \* Significant at the 10 percent level, \*\* Significant at the 5 percent level, \*\*\* Significant at the 1 percent level.

Table 5: Robustness Check: Influential Observations

	Dependent variable: Added Water in Milk in Percent					
	Drop N1	Drop N2	Drop N3	Drop N4	Drop N5	Drop N6
	(1)	(2)	(3)	(4)	(5)	(6)
Dishonesty	0.436*** (0.161)	0.467*** (0.155)	0.434** (0.201)	0.593*** (0.152)	0.330** (0.137)	0.476*** (0.142)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Time/ assistant FE	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	65.337*** (19.148)	48.583*** (17.551)	46.687*** (15.460)	41.449*** (11.792)	35.366*** (9.623)	46.081*** (13.691)
Observations	59	56	60	60	59	66
R-squared	0.55	0.57	0.49	0.64	0.59	0.58

Notes. OLS regression with robust standard errors in parentheses. FE stands for fixed effects. Columns 1-6 report estimates dropping one neighborhood (N) at a time. Covariates include price, age, high school, caste dummy, religiosity, buffalo herd size, and lactation period. \*\* Significant at the 5 percent level, \*\*\* Significant at the 1 percent level.

Table 6: Robustness Checks: Additional Controls

	Dependent Variable: Added Water in Milk in Percent						
	Feeding costs	State of origin	Outside option	Family size	Duration of stay	Neighbor's dishonesty	Luck
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dishonesty	0.467*** (0.157)	0.464*** (0.144)	0.457*** (0.144)	0.460*** (0.140)	0.461*** (0.145)	0.467*** (0.144)	0.466*** (0.140)
Feeding costs	0.292 (0.292)						
State of origin		0.025 (1.685)					
Outside option			-1.332 (1.490)				
Family size				-0.040 (0.260)			
Duration of stay					-0.107 (0.081)		
Neighbor's dishonesty						0.009 (0.165)	
Luck							0.040 (0.055)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time/ assistant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63	72	71	72	72	72	72
R-squared	0.62	0.55	0.55	0.55	0.56	0.55	0.56

Notes. OLS regression with robust standard errors in parentheses. FE stands for fixed effects. Nine observations are missing in column 1 as data on fodder costs were not available for these milkmen. Covariates include price, age, high school, caste dummy, religiosity, buffalo herd size, and lactation period. \*\*\* Significant at the 1 percent level.



Table 7: Binary Measure of Dishonesty, Measurement Error  
and Downward Bias

	Number of Over- reported Rolls	Added Water in Milk in Percent	
		Binary measure (1-percent)	
		Biased	Unbiased
	(1)	(2)	(3)
Strongly dishonest	17.088*** (2.521)	7.815*** (2.747)	9.407*** (2.805)
Weakly dishonest	3.825*** (0.834)		3.281** (1.472)
Covariates	Yes	Yes	Yes
Time/ assistant FE	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes
Constant	6.343 (7.340)	47.049** (13.482)	47.393** (11.654)
Observations	72	72	72
R-squared	0.77	0.52	0.56

Notes. OLS regression with robust standard errors in parentheses. FE stands for fixed effects. Covariates include price, age, high school, caste dummy, religiosity, buffalo herd size, and lactation period. \*\* Significant at the 5 percent level, \*\*\* Significant at the 1 percent level.



Figure 1: High density of dairy farms within a neighborhood



Figure 2: Customers lining outside the dairy to buy milk

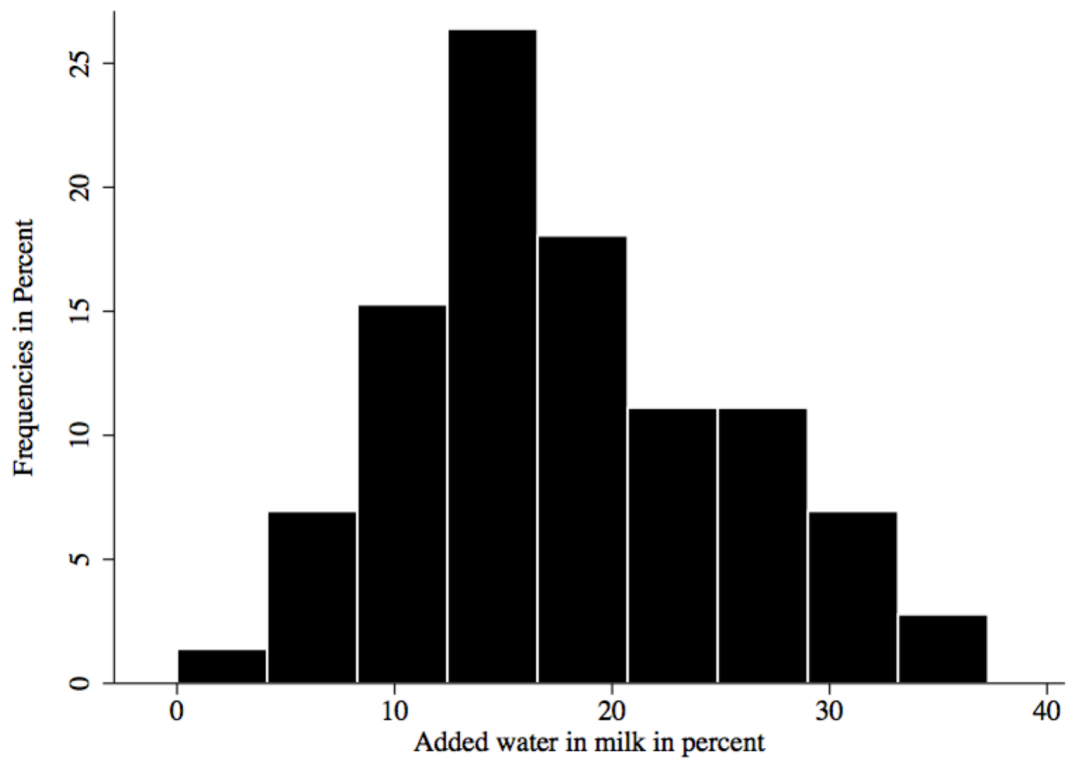
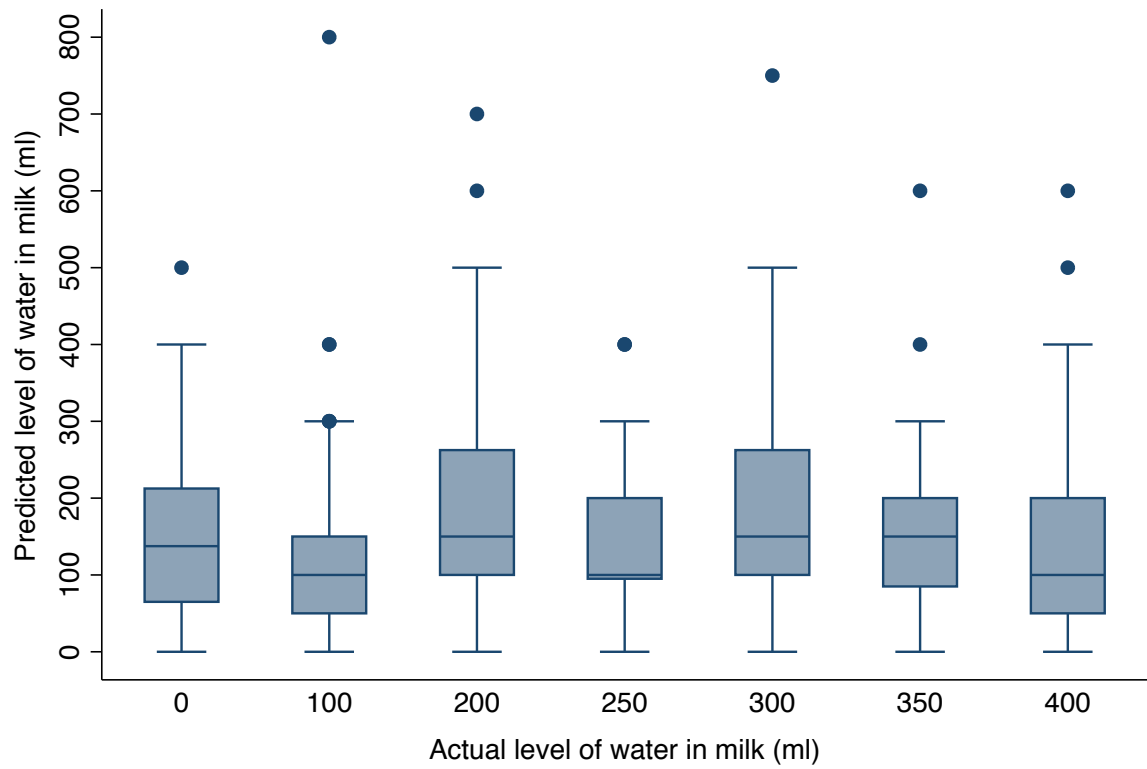
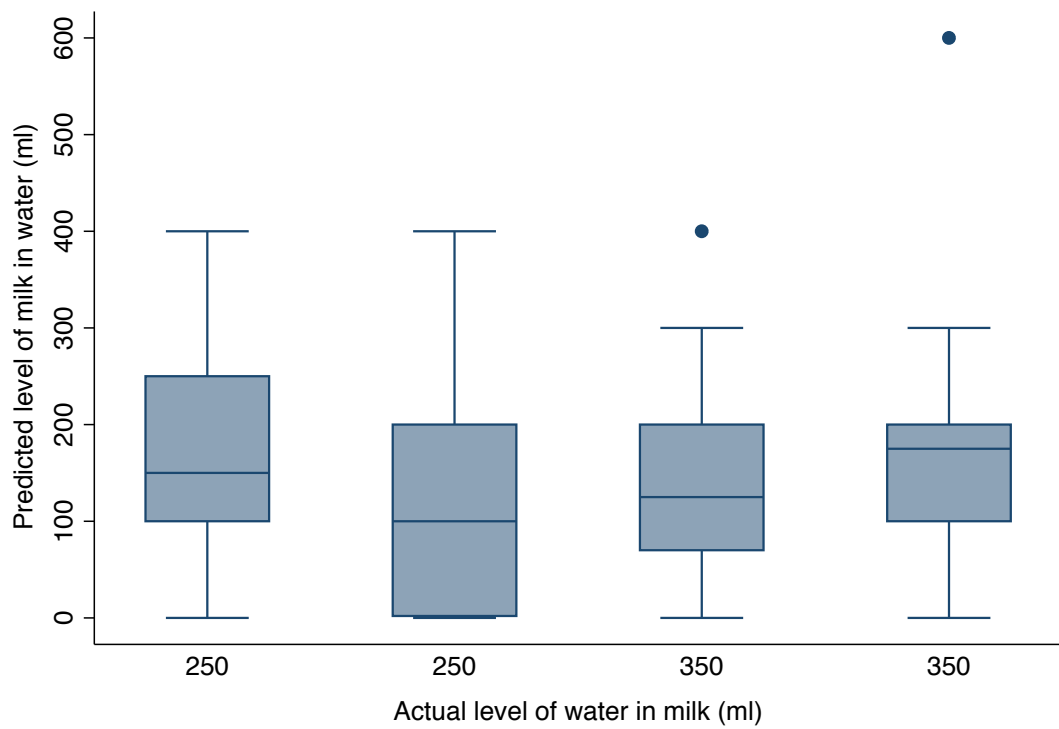


Figure 3: Distribution of added water in milk



(a)



(b)

Figure 4: Results from the milk-testing tournament

## ONLINE APPENDIX

### **Reputation, Honesty, and Cheating in Informal Milk Markets in India**

Markus Kröll and Devesh Rustagi

#### **Appendix A.**

##### **I. Procedures for Collecting the Main Outcome**

In this section, we provide a description of the procedures for collecting data on cheating in milk markets. It proceeds in two steps.

###### *Pilot study*

In the first step, we conducted a pilot study to identify different kinds of adulterants that milkmen may add to milk, as well as to validate the measure of added water in milk provided by the ultrasonic milk analyzer. This was done to avoid understating the extent of cheating for some milkmen by relying exclusively on added water as a measure of cheating in milk markets. We collected milk samples from 105 milkmen from neighborhoods in our study and tested these samples for a broader set of adulterants listed in the FSSAI study (2011). We split each sample into two parts. One part was sent to a professional food-testing laboratory in Delhi (Sima Lab Pvt Ltd.) to test for the presence of water, starch, urea, detergent, skimmed milk powder, and glucose. The second part was tested only for added water using the milk analyzer because the machine is unable to detect other adulterants. These analyses revealed that water is the main adulterant in milk in Delhi. Moreover, the correlation between estimates of added water by the laboratory and the machine is very strong ( $r = 0.93$ ). As a result, we focused on added water in buffalo milk in percent measured using the machine as our field outcome on cheating.

We rely on the machine measure because it allows for a more flexible, cheaper,

and precise analysis of added water. While the laboratory imposed a limit of 20 samples per week, charged INR 1,250 per sample, used a lactometer, provided mostly qualitative results, and took a week to deliver the results, the machine took only two minutes per sample to give the results.

### *Sampling procedures*

Milk samples were collected early in the morning (around 7 am) and in the afternoon (around 4 pm), shortly after the buffaloes are milked, in the third week of December. We hired assistants unknown to the milkmen to execute this task. In each neighborhood, every assistant purchased a liter of milk from five to eight milkmen spread out over several shifts. The set of milkmen for each assistant was assigned such that further contact with a given milkman was avoided after milk was bought from him. The purchased milk was then brought to a car outside the dairy and transferred into a clearly labeled plastic bottle, which contained a specific identification number for every milkman. These bottles were then stored in an icebox to prevent spoilage.

A major concern in collecting these milk samples is locating the dairy farms of the milkmen who took part in our experiment, because most milkmen do not have dairy names or addresses in front of their house. This could result in mismatching cheating in milk markets and dishonesty in the experiment. In order to avoid this problem, we prepared detailed maps of each neighborhood so that assistants could accurately locate the milkmen we wanted to target.

We prepared these maps (see Fig. A.1) through guided walks and photographs while conducting the second household survey. We marked every target milkmen on the map (e.g. color of the house, nearby shops, signs, and pole numbers, etc.). For particularly difficult matches, assistants were requested to take pictures of the dairy farm with their mobile phones, which were subsequently verified using pictures independently obtained by us.

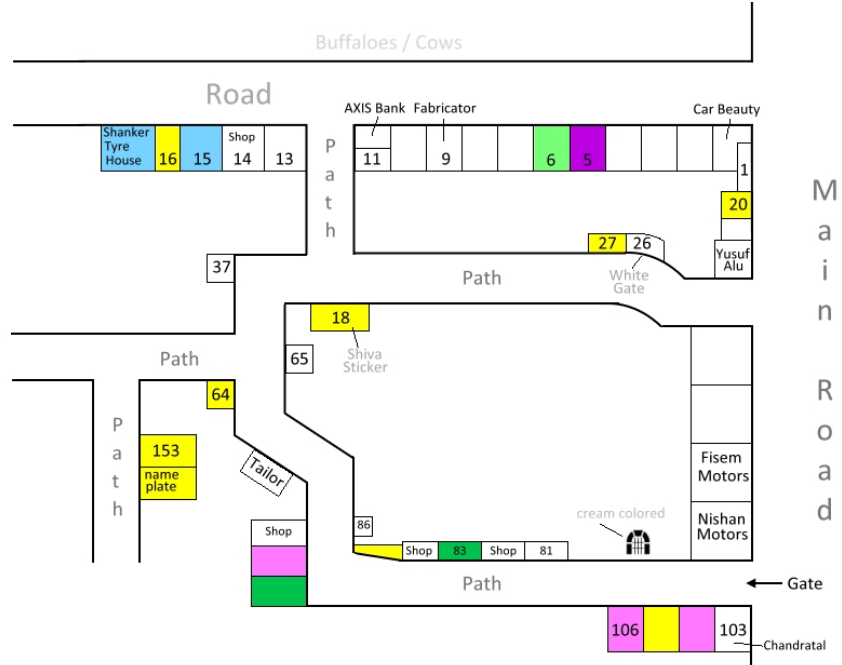


Figure A1. Map of a dairy neighborhood in our study

## II. Sample Construction

### *Selection into the experiment*

To control for the potential selection of milkmen into our experiment, we collected milk samples from 63 milkmen who did not take part in our experiment. These milkmen reside in the same neighborhoods and also operate small farms themselves just like the milkmen who took part in the experiment. The mean value of added water in milk is 17.96 for milkmen who took part in the experiment, whereas it is 19.05 for milkmen who did not. A regression-based test without or with controls for neighborhood fixed effects confirms that there is no difference in added water in milk across the two samples ( $p$ -value = 0.41). Similar, the average price for a liter of milk in the sample of milkmen who took part in the experiment is 57.72, it is 58.93 for milkmen who did not; these differences are not significantly different from zero regardless of whether the comparison is between ( $p$ -values = 0.30) or within neighborhoods ( $p$ -values = 0.66).

### Sample attrition

Despite our best efforts in collecting a milk sample from every participating milkman in our experiment, we could not obtain the field outcome for nine milkmen. In addition, we drop three milkmen for whom the actual outcomes in the experiment are missing due to outages in the Bluetooth-connection. Table A1 demonstrates that these 12 milkmen do not differ significantly from the 72 milkmen in our main sample in key socio-demographic characteristics.

Table A1: Sample Selection

	Participants in the sample (1)	Participants not in the sample (2)	Difference (3)
Self-reported sum	147.472 (21.504)	145.25 (21.872)	2.222 (6.721)
Age	33.847 (11.089)	32.583 (9.140)	1.264 (3.383)
Education	0.666 (0.475)	0.666 (0.492)	-0.000 (0.148)
Caste	0.569 (0.499)	0.583 (0.515)	-0.104 (0.156)
Religiosity	21.227 (36.707)	6.917 (8.670)	14.310 (10.696)
Buffalo herd size	18.778 (35.619)	9.25 (12.374)	9.528 (10.430)
Lactation period	0.792 (0.409)	0.556 (0.527)	0.236 (0.149)

Notes. We compare covariates across 72 milkmen who too part in our study (column 1) and 12 whom we excluded (column 2). Column 3 reports the difference using a regression-based test. Numbers in parentheses are standard deviation of the mean in columns 1 and 2, but standard error in column 3.

### III. Control Experiment

To control for a potential effect of the Bluetooth die itself on cheating behavior, we conducted a control experiment with 105 participants in which one half played the game with the Bluetooth die and the other half was given a regular die. Comparing the reported sum of points for the two groups reveals that the group which used the Bluetooth die does not differ from the group which played the game with a regular die. Testing for differences in the distribution across the two groups with a Kolmogorov-Smirnov test, we find no significant difference ( $p$ -value= 0.698). Similarly, the mean

across the group which used the regular die (158.88 points) is not significantly different from the mean across the group that used the Bluetooth die (153.49); the difference being 5.39 points, ( $p$ -value= 0.343).

#### IV. Dishonesty and Control Variables

Table A2 reports that none of the covariates are significantly correlated with dishonesty, measured as the number of over-reported rolls.

Table A2: Correlates of Dishonesty

	Dependent variable: Degree of dishonesty		
	(1)	(2)	(3)
Price	0.000 (0.183)	-0.001 (0.178)	-0.152 (0.171)
Age	-0.051 (0.052)	-0.070 (0.059)	-0.074 (0.058)
High school	0.721 (1.289)	0.791 (1.325)	1.013 (1.501)
Caste	1.721 (1.481)	1.686 (1.551)	1.317 (1.666)
Religiosity	0.015 (0.027)	0.010 (0.028)	0.026 (0.028)
Buffalo herd size		-0.006 (0.008)	-0.019 (0.013)
Lactation period		2.409 (1.585)	2.747 (1.755)
Fixed effects	No	No	Yes
Constant	3.556 (11.070)	2.527 (10.708)	9.665 (10.005)
Observations	72	72	72
R-squared	0.03	0.05	0.15

*Notes.* OLS with robust standard error in parentheses. Fixed effects include dummies for neighborhoods.

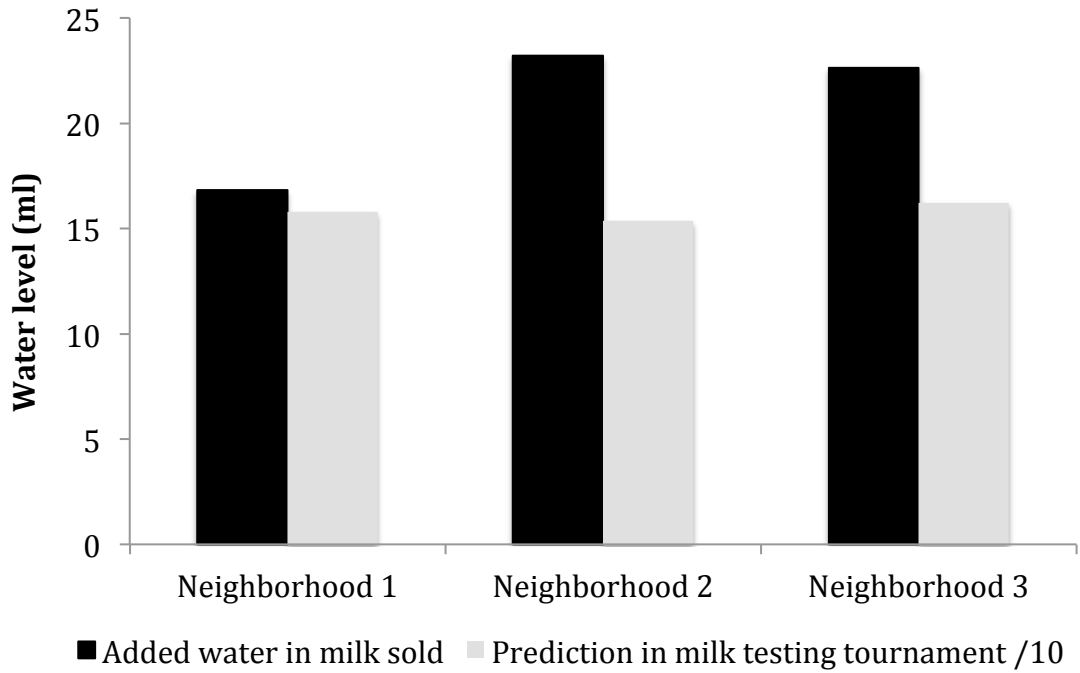
#### V. Milk Testing Tournament

In Figure A2, we show mean added water by milkmen in milk sold to customers by neighborhoods where the tournament was conducted alongside predicted value of water in the tournament. We find that although added water to milk sold to customers differs significantly across neighborhoods ( $p$ -value = 0.09), there is no difference in predicted value in the tournament ( $p$ -value = 0.85). A regression-based test in Table A3, whereby



we control for differences in actual levels of added water in the tournament confirms these results. The coefficients on neighborhood dummies are both individually and jointly statistically insignificant ( $p$ -value = 0.77).

Figure A2. Average added water in milk sold to customers by milkmen and predicted values in the milk-testing tournament by neighborhoods



*Notes.* Prediction in the milk-testing tournament is divided by 10 to allow for comparison with added water in milk sold.

Table A3: Prediction in Milk-Testing Tournament across Neighborhoods

	Dependent variable: Predicted Water Level
Actual Water Level	-0.01 (0.06)
Dairy 2	-3.70 (22.18)
Dairy 3	4.39 (26.66)
Constant	158.98*** (25.55)
Observations	370

*Notes.* OLS with robust standard errors clustered on the individual in parentheses.

In table A4, we show at the individual level that without or with controls there is no association of predicted water level with actual water level and added water to milk.

Table A4: Prediction in Milk-Testing Tournament  
and Added Water to Milk Sold

	Dependent variable: Predicted Water Level		
	(1)	(2)	(3)
Actual Water Level	0.095 (0.158)	0.095 (0.159)	0.095 (0.162)
Added water to milk		-2.482 (2.615)	-2.592 (3.968)
Other covariates	No	No	Yes
Constant	124.815* (67.294)	183.697* (86.215)	228.809 (163.906)
Observations	60	60	60

OLS with robust standard errors clustered on the individual in parenthesis. Control variables in column 3 include age and buffalo herd size. Education, Caste, and Worship are not included because of little variation in these variables in this sub-sample.

## VI. Selection into the Second Sample

In table A5 we test whether the milkmen for whom we have the second sample differ from those for whom we do not have the second sample along a number of important covariates. Our results show that the two groups of milkmen are comparable on

observable characteristics.

Table A5: Sample Selection-Second Milk Sample

	Coefficient on a dummy for the second sample
Devnum	-1.811 (1.748)
Price	0.443 (1.051)
Age	-0.353 (2.950)
Education	-0.158 (0.121)
Caste	0.098 (0.105)
Religiosity	2.517 (8.906)
Buffalo herd size	-7.826 (9.268)
Lactation period	0.116 (0.109)

Notes. OLS with robust standard errors in parenthesis. We compare covariates across 29 milkmen for whom we have the second sample and the remaining 43 milkmen for whom we do not have the second sample. Each row presents results from a separate regression of the covariate listed in the row on a dummy, which equals 1 if the second sample was obtained, otherwise 0. Controls include neighborhood fixed effects. The results remain unchanged when neighborhood fixed effects are dropped.

## VII. Robustness Checks – Bluetooth Misses

Table A5 reports several robustness checks that we conducted with respect to Bluetooth misses. It confirms that Bluetooth misses have no bearing on the interpretation of our results. In column 1, we present results from a regression in which each observation is weighted by the number of recorded rolls. In column 2, we directly control for the number of missed rolls. In column 3, we exclude observations for which we missed ten or more recordings. None of this has any major implications for our findings; the coefficient on the number of over-reported rolls is always close to 0.46 and remains highly significant. Even when we make the extreme assumption that milkmen always over-reported in all the missed rolls unless they reported a ‘1’, the coefficient on dishonesty remains highly significant at the 1-percent level despite a drop in its magnitude (column 4). In column 5, we weight the number of over-reported rolls

linearly by the number of missed rolls, i.e. we assume that a milkman's reporting behavior does not differ in recorded and non- recorded rolls. Lastly, in column 6, we use the actual outcome in all recorded rolls in our sample to calculate the average share of rolls in which over-reporting occurred conditional on each reported outcome. We then replace non-recorded rolls with these averages. As before, we find that the coefficient on dishonesty remains strong and significant. These results also hold when we use alternative measures of dishonesty.

Table A6: Robustness Checks: Bluetooth Misses and Cheating in Milk Markets

	Dependent Variable: Added Water in Milk in Percent					
	(1)	(2)	(3)	(4)	(5)	(6)
Dishonesty	0.460*** (0.154)	0.466*** (0.150)	0.420** (0.160)	0.302*** (0.104)	0.391*** (0.108)	0.452*** (0.135)
Bluetooth miss		-0.080 (0.199)				
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Time/ assistant FE	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	42.436*** (11.440)	46.179*** (13.070)	39.638*** (12.471)	44.557*** (14.763)	48.974*** (13.846)	44.672*** (13.388)
Observations	72	72	64	72	72	72
R-squared	0.57	0.57	0.55	0.50	0.56	0.55

*Notes.* OLS regression with robust standard errors in parentheses. In column 1, each observation on the number of over-reported rolls is weighted by the number of recorded rolls. Column 2 includes the number of missed rolls, i.e. the number of rolls in which the Bluetooth die did not transmit the outcome and an outcome larger than '1' was reported, as an additional covariate. All milkmen who had more than 10 missed rolls are dropped in column 3. For column 4, all missed rolls are added to the number of over-reported rolls. In column 5, the number of over-reported rolls is weighted linearly by the number of missed rolls. For column 6, we compute the share of over-reported rolls for each outcome of the die roll based on the observed behavior in the recorded rolls in our entire sample, and add the respective share to the number of over-reported rolls for the outcome of each missed roll. Fixed effects include dummy variables for the time of day milk was purchased, assistants, and neighborhoods. \*Significant at the 10 percent level, \*\* Significant at the 5 percent level, \*\*\* Significant at the 1 percent level.

## **Appendix B. Experimental Instructions and Procedures**

### **I. General Instructions (translated from Hindi)**

Greetings and welcome to all of you. My name is Devesh Rustagi and his name is Markus Kröll. We are working at a university in Germany. We are here for research on the livelihood of milkmen. We hope that you will help us with our study. Please switch off your cell phones now. We thank you a lot for your support.

1. In this research, we would like to play a few games with you. In these games, you can earn some money. How much you can earn depends on how you play the game.
2. In the games, your identity will be kept anonymous. I am interested only in the decisions made by you in these games and not your identity. This is the reason that we removed your plot number from your personal invitation card. We will identify your decision in the game with a sticker like this (show sticker). You will draw a sticker like this from a lottery and we will stick it to your personal invitation card. Please do not lose the invitation card.
3. We will play two different games with you. You can earn money in both the games, which we will pay you immediately after the games are over.
4. We will give you separate instructions on how to play each game. Before we play the first game, we will give you the instructions on how to play the first game. Likewise, when we play the second game, we will give you the instructions for the second game. It is very important that you listen to these instructions carefully. In case you do not understand the game, please do not hesitate to ask us. We will be happy to assist you.
5. Before the start of the actual game, we will ask some questions to verify that you have understood the game. Therefore, it is important that you pay attention to our explanations and instructions.
6. Please do not discuss the games with the other players.
7. Do you have any questions as of now? If not, then we will begin with the

instructions for the first game.

## **II. Instructions for the Die Game (translated from Hindi) Instructions die game**

1. You play this game on your own.
2. We will give you a die like this (show the die) and a sheet of paper like this (show the sheet).
3. All you have to do is to roll the die and report the number on the sheet of paper which we gave you.
4. To record the number, please cross INR 2 coins in the appropriate row. Each row has 6 coins, one coin for each point on the die (show it on the poster).
5. You get 2 INR for each coin you cross. Let's take some examples: Example 1: if you cross 2 coins, then we will pay you INR 4 (cross two coins on the poster); Example 2: if you cross 5 coins, then we will pay you INR 10 (cross five coins on the poster).
6. You will have to repeat this task 40 times.
7. Your final earnings for this game will be the sum of earnings in each of the 40 rounds. We will sum the total earning over all rounds for you.
8. This means, the minimum you can earn is 80 INR and the maximum is 480 INR.
9. You will play this game in a private cabin (show the cabin). Once you are done playing this game, please give the sheet to us.
10. Please leave the room. We will call you one by one.

### **Control questions (Individually)**

Do you have any further questions? If no, we will ask you a few control questions.

1. How many times do you roll the die?
2. How much money do you earn by crossing a coin?
3. How is your income calculated?

**Procedure (Individually)**

1. Please roll the die like this on the table (Demonstrate proper die roll).
2. If the die drops off the table, please do not record the outcome and repeat the die roll.  
Please make sure that the die does not drop.
3. After the game is over, please give us the sheet.

**III. Experimental Procedures**

In the following we briefly outline the procedural details of our experiment. The experiment was conducted within the premises of each dairy neighborhood a month before we collected the milk samples for the final field outcome. The experiment was scheduled such that participation did not overlap with the daily business of milkmen. We personally notified selected milkmen a few days before the experiment with the help of a community mobilizer from the respective dairy neighborhood. All selected milkmen were given a personalized invitation card containing their individual plot number in the dairy, which served as an admission to the experiment (Figure B1, top card). In addition, these cards enabled us to match experimental and field outcome. Each card had a unique ID number written on its back using a UV-readable pen. Thus, these IDs were invisible to the milkmen (Figure B1, middle card) and was only readable using UV-light (Figure B1, bottom card). We verified in the post-game interviews that milkmen did not exchange these invitation cards.

On the day of the experiment, we first carefully explained the purpose and procedure of the experiment at the group level. Each milkman then replaced his individual plot ID number with an identity card of his own choice bearing the names of European states (see Figure B1, top card). We then gave detailed instructions and examples at the group level for our die-game that were tested and polished in four pilot studies. Following these group-level instructions, every milkman was individually led into a room in which the experiment took place.

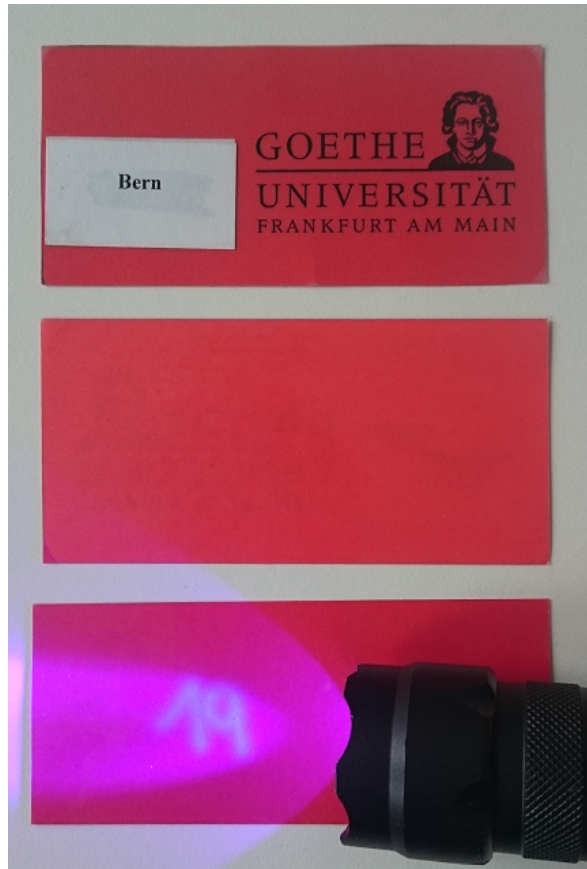


Figure B1. Invitation card

For the actual game we undertook great efforts to create the impression of full privacy: every participant was individually led into a room where they carried out the task on their own. Before milkmen took part in the actual experiment, they had to answer three control questions correctly and were once again shown how to roll the die (Figure B2). This individual demonstration was implemented in order to minimize deliberate manipulation of the die rolls, e.g. not rolling the die properly. We used a wooden table and a 5-row game sheet to keep track of the number of completed die rolls, which allowed us to obtain data on such deliberate manipulations (Figure B3). Limiting the number of rows to 5 per page allowed us to assess the progress during the experiment, whenever participants flipped a page. The wooden table ensured that each die roll was audible. One of the authors noted down the outcomes of each die roll transmitted by the Bluetooth die.





Figure B2. Bluetooth Die

After all milkmen within a neighborhood had completed the experiment, they were invited to fill a post-game questionnaire. Upon completion of this survey, milkmen were paid the sum of earnings plus a show-up fee of INR 200. On average, each milkman earned INR 495 (USD 8).

We also took great care to address the problem of contagion and contamination among milkmen. To mitigate this risk, we conducted the experiment with all milkmen from one dairy neighborhood on a single day and invited all of them at the same time. One of the authors and an assistant monitored their conversations and made sure that they did not discuss the experiment.

ID \_\_\_\_\_

Date \_\_\_\_\_

Roll Number	Die outcome
1	
2	
3	
4	
5	

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